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Emulation-based Uncertainty and Sensitivity Analysis of a multi-zone dwelling

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Abstract

Computer models of building thermal phenomena are increasingly coupled with the other domain specific models, for instance of occupants' stochastic behaviours, improving the plausibility of energy performance simulation results, but at the cost of increased complexity, in terms of the number of required inputs and computational expense. Model complexity may also result in unanticipated predicted behaviours, as the inputs are inherently uncertain. To improve the reliability of energy predictions under uncertainty, and thus to contribute to efforts to address the so-called energy performance gap, a pragmatic treatment of uncertainty in building energy simulation should: 1) simulate the involved thermal phenomena at an appropriate level of complexity, 2) rank the importance of and quantify the effects of parameters in the uncertain parameter space, accounting for their interactions, and 3) do this in a computationally tractable manner.

To this end, this paper introduces a new two-stage Emulation based Uncertainty and Sensitivity Analysis (EmUSA) framework. The first stage involves a systematic dimensionality reduction of the uncertain parameter space, by segregating the most influential parameters from their less-influential counterparts, using parameter screening. In the second stage a Gaussian Process emulator of a stochastic building performance simulator (EnergyPlus coupled with the Multi-Agent Stochastic Simulator No-MASS) is constructed and applied to the reduced parameter space, to efficiently perform a global uncertainty quantification study. After describing this new framework, we demonstrate its application to study both aleatory and epistemic uncertainty to inputs describing a multi-zone residential building energy model; closing with a discussion of the results.

Introduction

The sources of uncertainty resulting into *energy performance gap* between model prediction and measurement arise from the level of complexity with which a particular heat transfer phenomenon is modelled and the level of detail of input data / building information available to conduct a simulation study. The computational models of three fundamental heat transfer phenomena (conduction, convection and radiation) that dominate indoor energy balance constitute a Building Performance Simulation (BPS) model (Clarke, 2001). BPS tools are under continuous development and the model improvement efforts such as model calibration (Raftery et al., 2011) and post-occupancy evaluations (Menezes et al., 2012) have been contributing in narrowing down the *performance gap*. However, some of the causes behind the *gap* widening though are of perpetual nature depending upon the BPS case study and its designed objectives. The causes may include (Van Dronkelaar et al., 2016; Allard et al., 2018) - 1) errors or limitations in the abstraction and simulation of non-trivial phenomena such as bi-directional transient heat conduction through building elements, occupants' stochastic interactions and uncertain and dynamic ambient weather conditions, 2) use of deterministic schedules of building HVAC systems' thermostat and operation hours settings, 3) uncertainty about the variations in buildings' future functions / usages during design stages, 4) poor workmanship issues related to airtightness standards during building construction, 5) lack of conformance to the required level of insulation and 6) user data input errors and unavailability of detailed datasets regarding internal loads post-occupancy, building geometry, construction compositions, material properties, household compositions and the type of installed heating systems.

To improve the fidelity of BPS, there has been a recent shift toward stochastic building performance simulation paradigm where a simulation program or coupling platform attempts to integrate the models of stochastic processes such as occupants' behaviours (Chapman et al., 2018) and outdoor weather conditions (Rastogi, 2016) in order to represent and account for the detailed modelling complexity as demanded by the case study application. For instance, in a low energy building design scenario, for present and in future, the building envelope is expected to improve in terms of its energy efficiency thus exhibiting less dominating impact on energy balance however occupants' interactions with the envelope elements (such as windows and shades) may start to have an exaggerating impact due to internal heat gains being foreseen as an important factor in predicting energy performance (Robinson and Haldi, 2011). Stochastic Building Performance Simulation (S-BPS) model i.e. a co-simulation platform coupling Building Performance Simulation program EnergyPlus with Multi-Agent Stochastic Simulator No-MASS developed by Chapman (2017) offer one such instance of simulation complexity that attempts to contribute in addressing the *gap* by modelling inherent randomness of occupants' behaviours as stochastic processes. However, this poses a few challenges in accounting for an uncertainty mix comprising of epistemic (lack of knowledge about a true value of input parameters) and aleatory (due to occupants' stochastic interactions) uncertainty in the predictions of building energy performance (Wate, 2020) - 1) systematic identification of the sources of uncertainty for a given case study, 2) characterisation of the uncertainty mathematically, 3) their computationally efficient propagation from the sources through the model till the predictions, 4) numerical quantification and analysis of the uncertainty at source and prediction end and 5) finally decomposition of the prediction uncertainty into the respective sources that cause it.

This paper focus on the computationally efficient propagation of uncertainty through the S-BPS model of a relatively complex archetypal house along with accounting for the uncertainty in material thermophysical parameters, numerical quantification and decomposition of the prediction uncertainty. The next subsection presents the uncertainty problem of increased scope and complexity which is addressed by a two-stage workflow, extending the foundational EmUSA framework, which is introduced in the Method section. Thereafter, the results from the archetypal case study are discussed and the paper concludes with an outlook on the potential to further extend EmUSA framework for practical applications in building performance simulation. In particular, the framework has been envisaged to be a part of the Housing stock decarbonisation platform which is available on EnHub-UK GitHub repository (Sousa et al., 2018). This combined effort would then be able to aid decision makers to pursue various stock-scale decarbonisation pathways under uncertainty and also software vendors to implement the framework in their simulation software, upon furthermore experiments.

Simulation versus Emulation

Simulation and Emulation both abstract physical phenomena with former representing this abstraction in a differential equation form and latter approximating this statistically as a regression model. Emulator is essentially a data-driven statistical model which can be trained using either data generated by physics-based simulator or real-world measurements of phenomena. However, measurements are always limiting in terms of their representativeness, because of many practical constraints, to capture every other details in all the desired temporal resolutions. In addition, it is impossible to measure future energy performance. Here, physics-based simulator offer flexibility in terms of representativeness, granularity and future predictions. However, simulator often come with a computational burden, which is a crucial constraint in employing it for computationally demanding BPS studies such as uncertainty quantification. On the other hand, emulators are inexpensive in making a large number of predictions thus facilitating a global nature of uncertainty propagation and quantification. Emulators also possess interpolation and extrapolation capabilities enabling approximate predictions bounded by informative uncertainty limits at the sampling points for which training data is unavailable. To complement, in case of a typical calibration exercise where model parameters and inputs are retuned when more valuable data becomes available, emulators are only required to be retrained on new data which is incomparable to simulator in which some manual and at times iterative process is involved (Rastogi et al., 2017). Therefore emulating a representative simulator offers a computationally efficient alternative in plausibly approximating the simulator responses for this uncertainty quantification study.

Uncertainty problem

This paper proposes to extend the capabilities of EmUSA framework, developed and demonstrated in Wate et al. (2020), by accounting for a large number of uncertain input parameters along with occupants' stochastic interactions with windows and shades. This enhancement is of particular interest for the practical applications of framework where complex multi-zone case studies are under consideration for global uncertainty and sensitivity analysis. Specifically, the thermophysical properties (e.g. conductivity, heat capacity, density and thickness) of building envelope construction materials have been considered as uncertain variables for the analysis. The true value of material properties cannot be known a priori (say, in early building design stage) with exact certainty due to a number of reasons ranging from material manufacturing defects, change in material properties (before commissioning and installation) during storage and transport under varying ambient conditions and due to their quality assurance assessment techniques and measuring instruments' error / limitations (Hopfe and Hensen, 2011). For the purpose of demonstration of framework's extension, the uncertainty in material properties has been assumed to be characterised by assigning normal and uniform distributions to these variables and the distribution parameter values (e.g. mean, standard deviations, lower and upper bounds) based on the measured material properties documented in Clarke et al. (1990); Clarke and Yaneske (2009). The datasets have also been processed and utilised for the thermophysical variable uncertainty characterisation in Macdonald (2002); Domínguez-Muñoz et al. (2010). Zhao et al. (2015) have also developed a comprehensive material properties database for BPS studies [1]. As per these studies, a variability of 30% in thermal conductiv-

[1] Although beyond the scope of the present study, this more detailed database will likely underpin our future UQ studies in relation to material thermophysical properties.

ity values and of $10-12\%$ in specific heat capacity measurements and in the other properties around their base case values (Table 1) have been assumed. The infiltration rates (air changes per hour ac/h) for the zones of multizone house are also considered to be uncertain, normally distributed with $\mu = 0.4$ and $\sigma = 0.15$, with a goal to understand its impact along with the thermophysical properties. The model outputs of interest are annual heating Y_h and cooling Y_c energy demand per unit floor area.

Method

Coupling the detailed models of other thermal energy flow phenomenon such as the stochastic process models of occupants' behaviours with BPS programs can significantly increase the model complexity and computational expense in the simulation of building energy performance and that is in particular when the repeated simulations are required to adequately quantify these stochastic perturbations in simulation response. In addition, this expense is compounded when an uncertainty analysis study involves relatively large number of uncertain inputs to be considered (e.g. order of 10^2 in Spitz et al. (2012) on uncertainty analysis in building simulation). Moreover, if the study objective is to decompose prediction uncertainty (i.e. to know which amongst k inputs are the most influential) via a variance decomposition technique then the total computation cost is $N(k+2)$ simulations where N is the number of samples (as per theorem 1 stated in Saltelli (2002) on the extension of Sobol sensitivity analysis method (Sobol, 1993, 2001)). To this end, in order to increase the computational feasibility of conducting uncertainty and sensitivity analysis for complex building simulations, the methodology based on Gaussian Process (GP) emulators (see Rasmussen and Williams (2006) for technique) of mean and variance of building performance simulator responses have been developed in Wate et al. (2020). The GP metamodels for Y_h and Y_c are constructed to conduct sensitivity analysis for each output variable. These emulators are inexpensive and plausible substitute to the S-BPS model and have been effectively used to conduct numerical quantification and decomposition of prediction uncertainty. However, for the case of high dimensionality of uncertain input parameter space, this paper introduces a prior screening stage (Figure 1) based on Morris sampling and method (Morris, 1991) to the EmUSA workflow. This stage allows to qualitatively rank the influential input parameters so that for the next stage (Figure 2) they are the input to perform more rigorous global sensitivity analysis.

Methodology workflow

Substage 1A in Figure 1 prepares the sampling dataset for input parameters (in Table 1) using trajectory based Morris sampling design. Morris sampling trajectory in $k-$ dimensional input parameter space allows to cover the entire space more uniformly with less sampling points, unlike traditional one-at-a-time (OAT) sampling. A number of trajectories comprising of sampling points in input space has been generated depending upon the number of inputs and elementary effects to be computed per input. **Substage 1B** in Figure 1 An elementary effect per input for the number of sampling points on the trajectory has been computed as the ratio of difference in the model output between two sampling points to their difference in input values at the respective points. Each Elementary Effect EE_{kn} from the number of computed elementary effects per input is a value the EE_k random variable takes from the distribution comprised by them. This constitute a number of empirical distributions respective to each elementary effect random variable per input. Mean μ and standard deviation σ parameters of these respective empirical distributions per input define Morris measures and the variables for $\mu - \sigma$ plot. **Substage 2A** in Figure 2 is a training and test data preparation step which works on the p influential input parameters identified from initial k inputs. This step involves automatic parametrisation of EnergyPlus input data files based on the sampled data values and then conduct of S-BPS model runs on HPC. **Substage 2B** in Figure 2 constructs (from training data) and validates (using test data) a pair of GPs each corresponding to mean and variance of stochastic output responses Y_h and Y_c. Finally, a large number of inexpensive (and plausible) runs of these GP emulators have been conducted for the prediction uncertainty decomposition.

Case study description

A model of a relatively geometrically complex [2] multizone residential building located in Nottingham, UK ($51.15°N, 0.18°W$, elevation 62m) has been employed. This building consists of two occupied floors and an unoccupied attic having floor dimensions 7.4m×4.4m, and ceiling heights of 3.5m each and an attic floor with height of 1.45m (Figure 3). The wall, roof, ground and window construction compositions used in this study are given in Table 1. The sensible internal heat gains for a couple residing in this house are taken from ISO 7730 (ISO, 2005) depending upon their activity (e.g. sleeping (46W), passive (58W), TV (70W), IT;cooking;cleaning;washing (116W) and metabolic (93W)) and location (Bedroom, Living Room, Office, Kitchen) specified in Chapman (2017). The heating (and cooling) and ventilation set-point temperature schedules are set to 21°C (and 25°C) and 24°C during zone occupation hours, according to ASHRAE Standard 90.1 for a residential prototype building model (ASHRAE, 2018), representing an ideal loads HVAC system operation.

[2] at least, more so than the simple shoebox office building which formed the basis of the proof of principle of the EmUSA framework in Wate et al. (2020)

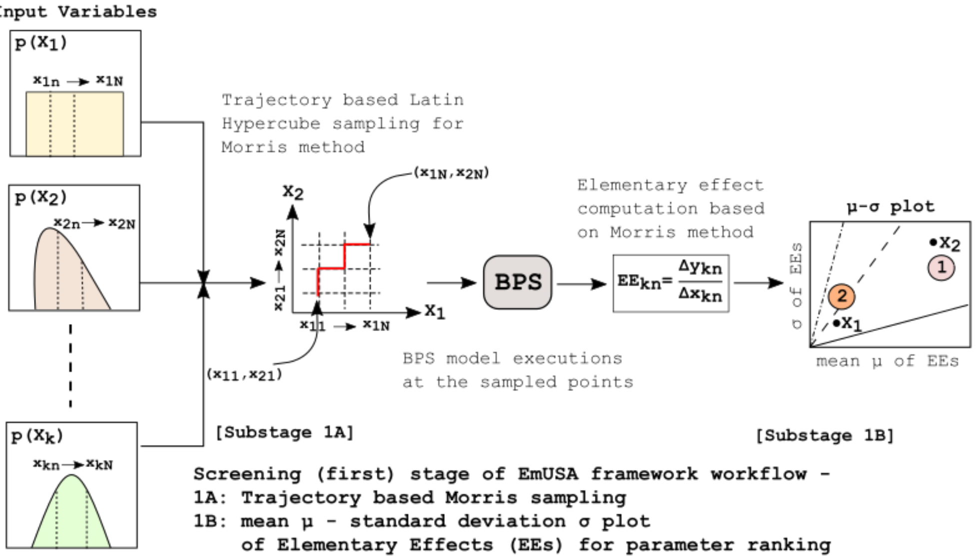

Figure 1: Parameter screening stage for dimensionality reduction in case of high dimensionality inputs space

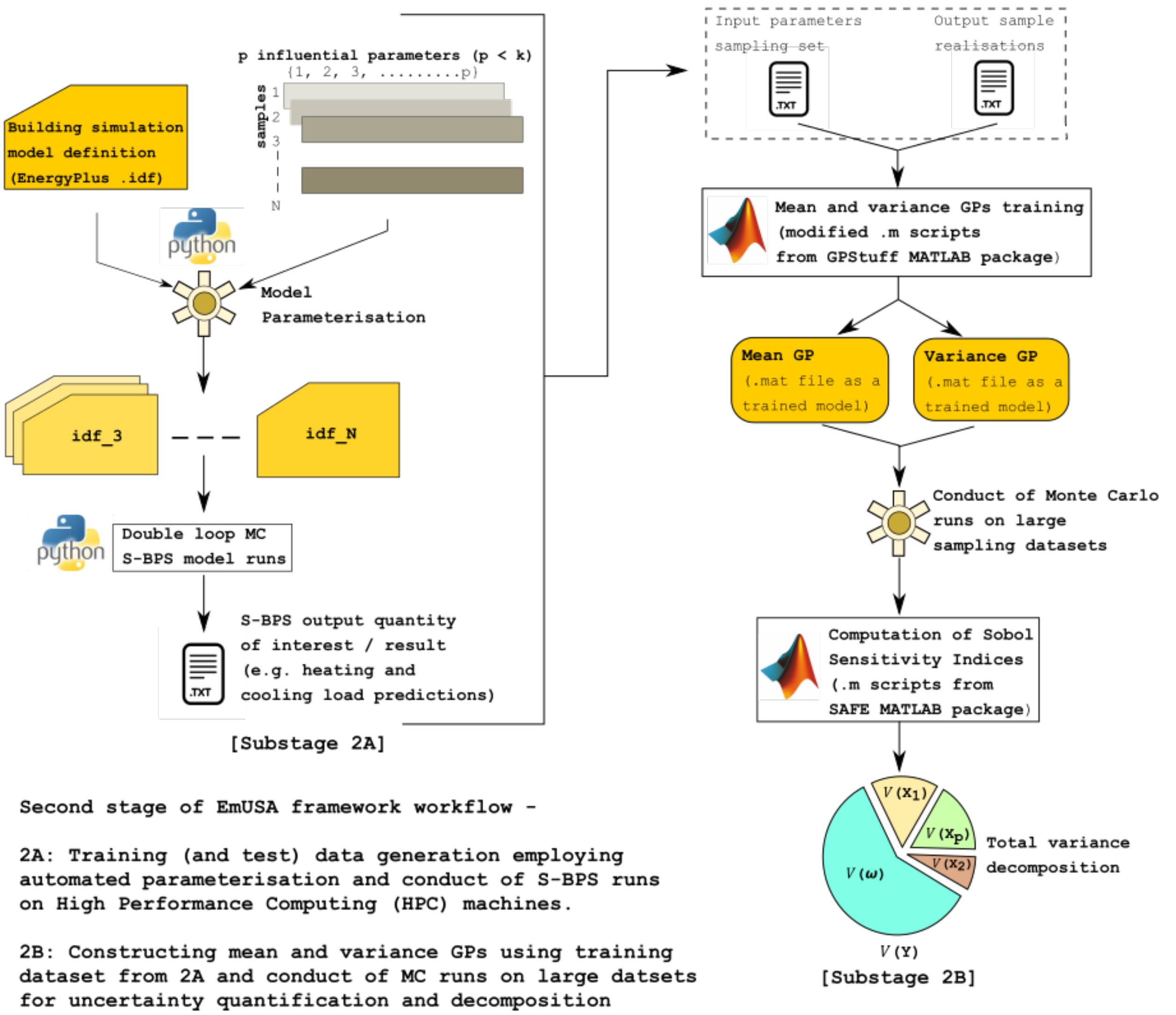

Figure 2: Second stage involving automatic parameterisation based on influential parameters and Gaussian Process construction of mean and variance responses for uncertainty quantification

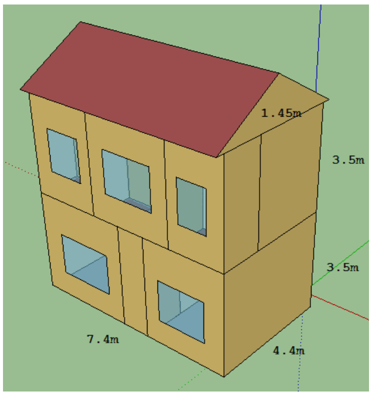

Figure 3: Building model of multizone house

Table 1: Thermophysical properties of construction layers : thickness t(m), thermal conductivity λ(W/(mK)), specific heat capacity C(J/(kgK)) and density ρ(kg/m^3)

Material (Surface)	t	λ	C	ρ
Brick (Wall)	0.1	0.84	800	1700
Insulation	0.0795	0.034	1400	35
Concrete	0.1	0.51	1000	1400
Plaster	0.013	0.4	1000	1000
Foam (Ground)	0.1327	0.04	1400	10
Concrete	0.1	1.13	1000	2000
Screed	0.07	0.41	840	1200
Flooring	0.03	0.14	1200	650
Clay tiling (Roof)	0.025	1	800	2000
No mass	Thermal Resistance= 0.15			
Felt	0.005	0.19	837	960
Glass (Window)	0.003	0.9	750	2500
Air	0.013	0.0262	1005	1.17
Glass	0.003	0.9	750	2500

Results and discussion

Parameter screening

Following Morris screening method, a qualitative analysis has been conducted to identify the most influential parameters out of fifty-nine considered uncertain parameters - thermophysical properties of materials such as brick, polystyrene insulation, concrete, plaster, urea formaldehyde foam, screed, flooring, clay and glass used in wall, ground, roof and window construction. With a number of elementary effects (= 10) to be computed for each parameter and for the total of fifty-nine parameters, a total 600 runs (samples obtained according to Morris sampling) of BPS model of multizone house have been conducted. Morris screening method is applied on this input-output dataset and the μ-σ (mu-sigma) plots for the heating and cooling demands are obtained (Figures 4 and 5). A mu-sigma plot qualitatively compares the parameters on account of their means and standard deviations obtained from elementary effects distribution. A number of elementary effects (=10 assumed for this study) are actually a number of samples drawn from

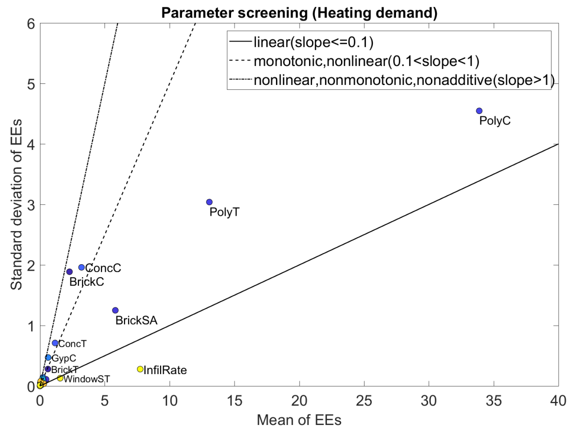

Figure 4: mu-sigma plot : Heating demand

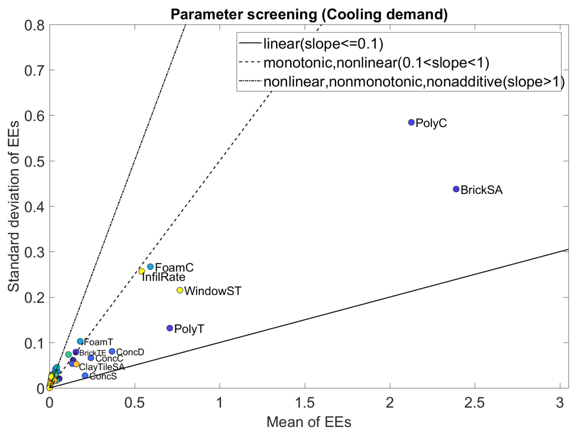

Figure 5: mu-sigma plot : Cooling demand

the elementary effect distribution for that parameter and these realisations when conducted determine the elementary effect distribution. Mean μ parameter accounts for the main or individual effect and standard deviation σ parameter for the interaction effect due to the impact of a combined variation in two or more interacting parameters on the model output. A high value for these parameters indicates higher influence on the output variable of interest. Table 2 describes the short annotations used for the parameters.

Morris measures aid in understanding the model behaviour as well as to compute the qualitative ranking of influential parameters. Sanchez et al. (2014) introduced an indicator $\frac{\sigma}{\mu}$ to detect the underlying model behaviour with respect to the parameters that causing the variations in model output. The three lines on the mu-sigma plots are the slope lines representing slope values $\frac{\sigma}{\mu}$ less than 0.1, between 0.1 and 1 and greater than 1. A solid line (slope $\leq$ 0.1) represent a linear response of model output to its inputs i.e. the parameters lying in the region below this line exhibit linear impact. This is because the deviations in elementary effect are so small that all the effects are very close to their mean or are constant depicting linear response with respect to the parameter. The parame-

Table 2: The uncertain parameters' annotations and their descriptions, used in these plots.

Annotation	Description
PolyC	Wall insulation Conductivity
PolyT	Wall insulation Thickness
ConcC	Wall Concrete block Conductivity
BrickC	Brickwork Conductivity
BrickSA	Brickwork Solar Absorptance
InfilRate	Infiltration Rate
ConcT	Wall Concrete block Thickness
GypC	Gypsum plastering Conductivity
BrickT	Brickwork Thickness
WindowST	Window Solar Transmittance
FoamC	Ground insulation Conductivity
FoamT	Ground insulation Thickness
ConcD	Wall Concrete block Density
ConcS	Wall Concrete block Sp. heat cap.
ClayTileSA	Clay Tile roofing Solar Absorptance
BrickTE	Brickwork Thermal Emittance

ters in the region between the solid line and dot-dash line (i.e. slope between 0.1 and 1) have monotonic to almost monotonic and nonlinear response. Because there are low to high deviations in effects (+ve/-ve) resulting into monotonically increasing or decreasing effect of parameter on the model output. The parameters in the region represented by the line with slope more than one exhibit most diverse behaviour of nonlinearity, non-monotonicity and non-additivity on the model output, as the elementary effects deviate highly from their mean. In case of heating demand (Figure 4), the parameters PolyC and PolyT (having high values for both mean and standard deviations) have highest impact, exhibiting monotonic and nonlinear impacts. Conversely, the WindowST and InfilRate having lower and linear response to the heating load predictions than PolyC and PolyT and while brickwork and concrete conductivity having more nonlinear impact. For cooling demand (Figure 5), again the PolyC and a new parameter brickwork solar absorptance BrickSA dominate. The other parameters FoamC, InfilRate, WindowST and PolyT indicating monotonic and nonlinear trend. From this qualitative analysis and plots, a total of eight (identified in **bold** in Table 2) most influential and common (to both heating and cooling demand) input variables have been selected for further extensive uncertainty quantification and decomposition.

Sensitivity analysis using the GP emulator

The total uncertainty in energy demand prediction has been decomposed using the individual and total effect Sobol sensitivity indices. The individual effect indices account for the impact of input variables and the total effect index includes that of occupants' behaviour. The index scale is between 0 and 1, with highly influential factors having values close to unity.

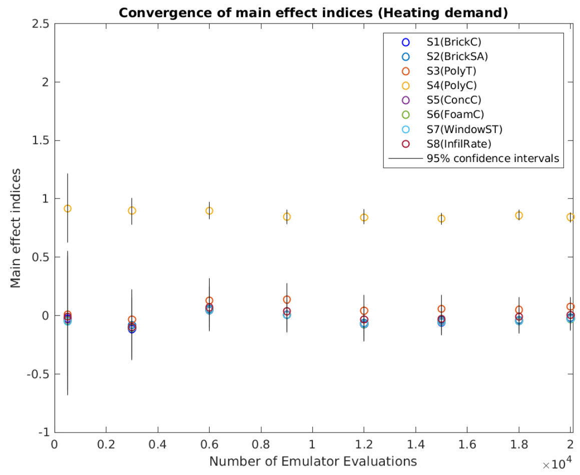

Figure 6: Convergence of main effect indices at distinct sample sets of increasing size : Heating demand

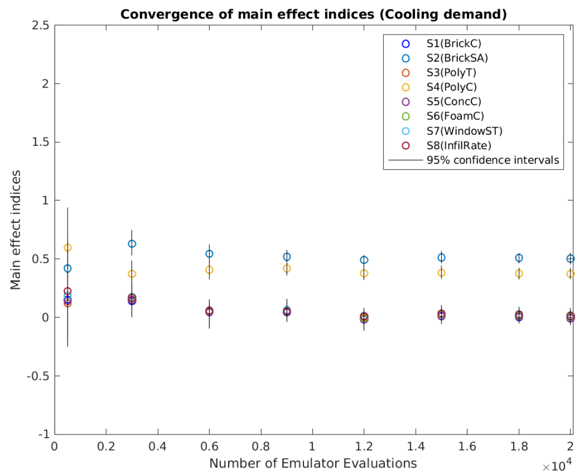

Figure 7: Convergence of main effect indices at distinct sample sets of increasing size : Cooling demand

In the case of heating demand, epistemic uncertainty due to PolyT and PolyC dominates the uncertainty in predictions, at the individual / main index values of 0.0771 and 0.8428 respectively (at the sampling set size of 20000 shown in Figure 6). For cooling demand, the parameter BrickSA (main index = 0.5032 in Figure 7) related to heat radiation components is dominant than aleatory uncertainty due to occupants' behaviour. Again, these quantitative analysis results highly corroborate with the qualitative analysis results (Figures 4 and 5), indicating PolyC and PolyT being the most influential parameters for heating and PolyC and BrickSA for cooling demand predictions.

Figures 8 and 9 show the combined sensitivity analysis of energy demands as a tornado plot. The tornado plots further reinforce the parameter screening results and obtained sensitivity indices showing that the occupancy stochastics, brick (BrickC) and concrete (ConcC) conductivities leading to negligible

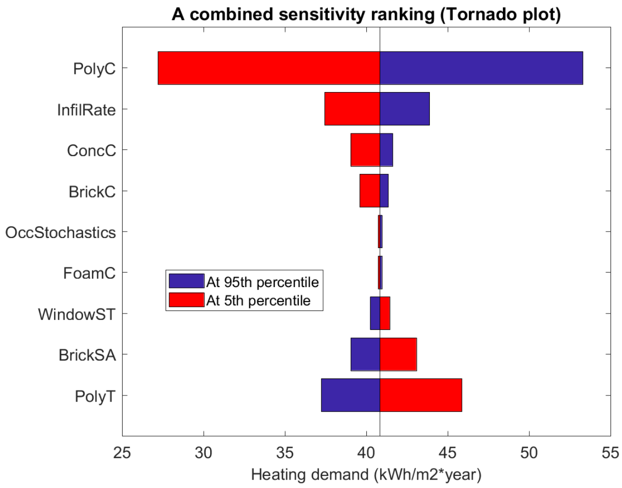

Figure 8: Tornado plot for heating demand

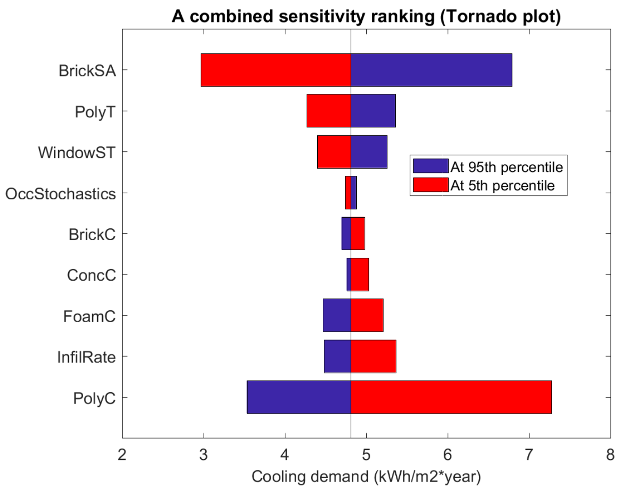

Figure 9: Tornado plot for cooling demand

variation in energy demands. For both output variables, the input variables PolyC, InfilRate, BrickSA and PolyT are the common variables that result into highest possible variation in energy demands. In fact, the tornado sensitivity analysis results are also consistent in their ranking of importance (with the ones in Figures 4, 5, 6 and 7). The heating demand is positively correlated with the PolyC and InfilRate (5^{th} percentile falling left of median) and negatively with the BrickSA and PolyT (5^{th} percentile falling right of median) (Figure 8). The polarity of correlation for these same input variables is reverse for cooling demand (Figure 9). The FoamC and WindowST exhibiting moderately negative and positive respective impacts on the cooling demand while negligible on the heating demand.

Conclusion and future work

The purpose of this case study was to demonstrate the applicability of EmUSA framework to support epistemic and aleatory uncertainty quantification for the models of increasing complexity. From these results we conclude, for this specific case study located in Nottingham, that:

- The effects of envelope heat losses and thus impact of uncertainty in wall insulation conductivity and thickness on heating demand are more significant than those arising from stochasticity in occupants' behaviours; as these behaviours to open windows (to avoid excessive heat losses) and to lower shades (thus reducing useful transmitted solar heat gains) are relatively constrained during the heating season.
- In case of cooling demand, the effects of uncertainty arising from brickwork solar absorptance and wall insulation conductivity dominate over the stochasticity in occupants' behaviours. This is due to conductive heat transfer through the walls dominates over transmitted solar irradiation during the moderate periods of cooling demand, for this temperature (and rather cloudy) climate.

These conclusions on occupants' insensitivity due to low levels of variability in occupancy, relative to other involved uncertain parameters, are also on the similar lines as from multizone medium office building case study in Wang et al. (2016) when aggregated seasonal energy consumption was also the output of interest. The sensitivity analysis for peak energy demand variable may result in conclusions otherwise due to the nature of occupants' behaviours and dynamics involved therein which can be further investigated using proposed framework. The current development of the framework is rigorous and comprehensive in addressing the varying type (epistemic and aleatory) and nature (simple design parameters to complex thermophysical properties) of uncertainty involving complex BPS model, however only at building scale. The next phase of development will focus on scaling up of uncertainty from building to housing stock scale. For its enlarged scope to handle the building archetypes, EmUSA framework would require to emulate the energy dynamics of housing stock and subsequently will then be readily exploited for practical applications for instance such as more robust new building design and energy-efficient improvements for retrofit design.

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